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Modeling behavioral synchronization in a joint tower-building task

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Abstract - **Human to Human sensorimotor interaction can only be fully understood by modeling the patterns of bodily synchronization and reconstructing the underlying mechanisms of optimal convergence. We designed a cooperative tower-building task to address such a goal. We recorded upper body kinematics of dyads engaged in the task, focused on the velocity profiles of the head and wrist, and applied Recurrence Quantification Analysis to examine the dynamics of synchronization within, and across the experimental session, comparing the roles of leader and follower. Our results show that the leader was more auto-recurrent than the follower to make his/her behavior more predictable. When looking at the cross-recurrence of the dyad, we find different patterns of synchronization for head and wrist motion. On the wrist, dyads synchronized at short lags, and such pattern was weakly modulated within a single trial, and invariant across the session. Head motion instead, synchronized at longer lags, a phenomenon mostly driven by the leader, and increased both within and between trials. Our findings point at a multi-scale nature of human to human sensorimotor convergence, and provide an experimentally solid benchmark to identify the basic motion primitives maximizing the coupling between humans and artificial agents.**

Index Terms — **Human-human interaction, Human-robot interaction, Body motion capture, Automatic imitation, Sensorimotor convergence, Joint action, Mirror neurons, Cross-recurrence quantification analysis, Dynamical systems**

I. INTRODUCTION

HUMANS are fundamentally tuned to detect human motion [1]. Such detection is directly based on biomechanical properties of the human body from which motor primitives can be extracted and used to temporally coordinate joint actions [2], as well as, convey the social dimension underlying the interaction taking place [3]. Importantly, motor information is obtained through mechanisms of "convergence" or automatic imitation unfolding during naturalistic interaction [4]. This idea is supported by research on the neurobehavioral mechanisms underpinning such imitative phenomena, i.e., observing other's actions primes similar actions in the observer [5].

More crucially, perhaps, sensorimotor convergence is assumed to facilitate interaction among humans in any goal-directed coordinative task. However, a key challenge is how to evaluate the coordination strategies used by interacting partners to achieve effective sensorimotor cooperation. One aspect of interpersonal coordination that has been received significant interest is the role of signaling [6]. During a joint action task, participants modulate position-based kinematic parameters to provide partners with hints concerning the specific action to be performed, among few alternatives. Imitation is observed when the participant acted in the role of follower [7]. An additional component is related to how leader–follower sensorimotor communication strategies evolve in time. Leaders' movement strongly affect the followers' imitative behavior, and the signaling strategy of the leader improve the dyad performance. Interestingly, leaders' signaling is informed by past interaction history [8].

Unfortunately, research on Human-Human Interaction (HHI) has often provided limited support to the design of Human-Robot Interaction (HRI) systems. In HHI research, experimental control usually imposes task-specific constraints on the context of interaction, and behavioral convergence is measured on few pre-defined variables (i.e. reaction times, hand opening, wrist elevation, etc) matching few selected and very specific task characteristics. As a consequence, potential HRI applications are constrained by the narrow context and measures implemented in the corresponding HHI scenario [9-10]. In order to extract useful information from HHI paradigms, a larger context independency is necessary.

Context independency may not be easy to achieve, given human behavior variability and flexibility. However, it is worth mentioning that automatic imitation itself is a multi-level phenomenon. Imitation can be centered upon high-level

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behavioral goals, leaving intact the detailed means to achieve them. At the opposite extreme, evidences suggest that fine-grained kinematic details of an observed action, irrelevant for goal achievement, are also automatically encoded and bias motor execution [11-12]. For example, the velocity profile of participants' movements can be influenced by the velocity profile of a moving dot [13]; an effect which is reduced when interacting with a partner who violates the biological laws of motion [14]. This suggests that low-level sensory-motor matching mechanisms can still affect movement planning and execution during joint action. More importantly, velocity profiles are independent from position data and thus, far more robust to variations induced by the task. At the same time, the analysis of velocity profiles can play a key role in characterizing movement control parameters that are known to show no context dependence [15].

A further possibility to achieve greater context independency may reside on shifting the study of human motion to a dynamical system approach, which deals with both the stability and the flexibility of coordinated actions at once [16-17]. This approach considers individuals and their interaction context as a coupled dynamical system, with coupling being both informational and mechanical in nature. Thus, interpersonal coordination results from individuals decoding others movements by taking into account task and context constraints, as well as, the mechanical limitations of their own actions [18]. Therefore, joint action is an emergent property arising from the informational couplings between individuals, and between individuals and the environment.

In this study we investigate the emergence of lower-level sensorimotor coupling, in a complex interactive task. Here we aimed at: (1) deriving quantitative measures of behavioral coupling; (2) tracking how such measures change over the course of few trials and (3) uncovering the behavioral strategies of the dyad, which improve joint task performance. In order to achieve these goals, we paid special attention to three key issues.

The first one regards task design. Discrete and rigid turn-taking tasks are often employed in standard joint action literature [19-22]. Such tasks have the clear advantage of granting perfect experimental control, but they usually focus on very specific movement features (e.g. hand-object contact, maximal finger aperture, curvature of arm trajectory, arm elevation, etc.), thus missing the whole complexity of the behavior. We devised, instead, an interactive task allowing continuous and temporally overlapping behavior [20]. In fact, the turn-taking behavior required in our task involve whole upper-body motion including arm reaching, hand grasping, body sway etc. More importantly the analyses are centered upon the velocity profile throughout the task, as opposed to discrete and pre-defined events.

The second critical issue relates to the features of the movement we focus on. Most studies examined the movement of a single body part [6-8,19-22] as opposed to capturing the overall movement of the dyad. Head motion, for example, is often considered an ancillary movement mainly assumed to convey emotional states or joint task engagement [22]. Head motion can be captured very easily either using dedicated motion-tracking systems [23] or applying video-based tracking algorithms [24]. Nevertheless, most studies focused on movements of body parts that are instrumental to the task execution (e.g., wrist) and derived measures of coordination constrained by the characteristics of the task. However, recording of instrumental movements for certain tasks, such as fingers tracking during joint object manipulation, might be challenging without specific technologies (e.g., data-glove). The tower building task presented in this study instead, solely requires active cameras providing distal recording [25]. Differently from previous work that has focused on a single body part [20], we focus on wrist and the head, and investigate whether their synchronization dynamics points at different functional roles of these two body parts, evolve along different time-scales, and inform us about the leader/follower relationship subsumed in our task.

The third critical issue regards choosing a methodology to quantify coordination. Previous work by some authors of this study applied Granger's causality [21,26] to derive patterns of cause-effect and obtain an indirect measure of sensorimotor information flow. In the current study, our interest is to measure kinematic similarity between participants to underpin processes of automatic imitation. A simple, and most commonly used method is cross-correlation, which we adopted on a previous study to show that the time-lags of maximal correlation in the wrist velocity profiles of the dyad get shorter across trials. A result demonstrating that the coordination of joint actions is achieved through the automatic imitation of low-level motor control parameters [20]. Here, we decided to utilize Cross-Recurrence Quantification Analysis (C/RQA), which is often referred to as a generalization of lagged cross-correlation and provides an additional range of different measures, beyond mere correlation, characterizing the non-linear dynamic patterns underlying joint interaction [27,28]. Recurrence Quantification Analysis [29] (RQA) is a technique originally developed in the natural sciences to capture recurrence in signals distributed over time (e.g, seismograms). RQA has been also used in cognitive science research to examine synchronization in behavioral information streams, such as body sways or gestures, which are the type of responses investigated in the current study [30,31] (for a review see [32]).

In summary, the main aim of this study is to investigate mechanisms of bodily alignment during a collaborative tower block-building task, where a leader/follower relationship is alternated at every session (the reader is referred to section Procedure for more details about the task). In particular, we sought to examine whether different parts of the body (e.g., head and wrist), would display a similar pattern of alignment, whether they vary between leader and follower, as well as, track how mechanisms of alignment change due to learning experience. Specifically, we formulate two hypotheses. The first one is that the leader and follower will modulate their predictability across trials and also within a single trial to offer social affordances to their collaborator. This hypothesis follows from previous literature on interpersonal interaction showing that dyads engaged in collaborative tasks tend to align their responses to maximize mutual understanding and optimize task performance [8]. Secondly, we predict that such pattern will dissociate instrumental movements (Wrist) from ancillary ones (Head). This prediction is supported by previous research which found partial dissociation between interpersonal coordination at the level of keystrokes and body movements (head and torso) in piano duet [33].

II. Methods

A. Participants, task and data

Forty-six participants (23 males and 23 females) were recruited among the Italian Institute of Technology staff members (mean age 29.26; SD = 2.92) to take part into a tower building task, where 12 colored cubes had to be stacked in a tower shape by a dyad of participants (6 each) in a turn-taking fashion. Each dyad performed the task 10 consecutive times, and each participant of the dyad alternated the role of "leader" (i.e., the one who began the cube sequence) or "follower" (i.e., the one who "followed" the color chosen by the leader), playing a total of 5 trials in each role; please refer to [20] for more details. The protocol for this study was approved by the local ethics committee (ASL-3, Genova), and the experiment took about 10-15 minutes to complete. We recorded the body movements using a motion capture system (VICON system) with 9 near infrared cameras at a sampling rate of 100Hz. Reflective markers were placed on: both shoulders, the dominant arm, elbow and wrist, and on the head (see [20]). From a total of 230 trials (23 dyads over 10 sessions), 40 trials were removed from the analysis due to inability to complete the tower. Thus, the results are based on 190 unique trials.

B. Recurrence analyses

As mentioned above, we use C/RQA to capture the sensorimotor dynamics of bodily coordination during dyadic interaction. The recurrence plot (RP) is the basic component of C/RQA, which is obtained by taking a time series X(t) (e.g., the velocity profile of the head), generating delayed copies $X(t + \tau)$ by introducing a lag τ into it, and calculating the euclidean distance between the original and the delayed time series. Time-series can also be embedded into higher dimension by simply multiplying τ by a constant m, $X(t + m\tau)$. Two points are considered recurrent if the distance between the original and delayed copies fall within a certain radius. From RPs constructed either on a single time series (i.e., auto-recurrence) or between two different time series (i.e., cross-recurrence, CRPs), we can compute several measures characterizing the behavior of the system (e.g., the alignment of head movement in a dyad). The most general measure that can be computed from RPs is recurrence rate (RR), which refers to the amount of overall recurrence in the plot. This measure, however, is rather general and indiscriminate, because it does not take into account the directionality of alignment, which is particularly important when examining the pattern of synchronism arising between different time-series. In fact, measures computed along the diagonal and vertical lines of a C/RP can tell us very different things about the dynamics of the system. Along the diagonal lines, we can observe the synchronism of a system, along the vertical lines, instead, the persistency of the system. For this reason, along the diagonals we focus on: (a) the average length of the diagonal (L), which reflects the regularity of the system (longer lines imply longer synchronization), (b) the percentage of recurrence points forming diagonal lines (DET), which reflects the predictability of the system (the higher the value, the more predictable the system is), and (c) the entropy of the line distribution (ENTR), with high entropy indicating a more complex pattern of synchronization than low entropy (where diagonal lines tend to have the same length). On the vertical lines, we focus on (d) the laminarity (LAM), which indicates the intermittency of the system, i.e., how likely is the system to persist, or not, in the same state (lower laminarity higher intermittency).

Moreover, changes in recurrence can also be tracked along the time-course of a session using a windowed approach [34]. This approach makes possible to establish how synchronism between the two agents develops as their interaction progresses. In particular, C/RQA measures are calculated in overlapping windows of a specified size for a number of delays smaller than the size of the window. In the context of this study, we use windowed cross-recurrence to uncover whether head and wrist display the same pattern of alignment, or not, within a single session, and how it changes as a result of learning across sessions.

We apply RQA and CRQA on velocity profiles obtained from two body markers, one placed in the front of the head, and the other one placed in the wrist of the two participants. First, we interpolate (down-sample, up-sample) all the velocity profiles for the head and wrist data, such that we standardize the duration of all trials. Then, we use RQA to measure the patterns of auto-recurrence, separately for leader and follower, so that we can compare whether follower and leader differ in how they adapt to the task. We apply C/RQA between leader and follower to capture their pattern of synchrony. We focus, and report, the four measures of L, DET, ENTR, LAM, detailed above. When dealing with continuous valued time-series, such as body sways, the parameters of radius, embed and delay have to be estimated from the data, by following principles of phase-space reconstruction (refer to [35] for more details). Briefly, delay is computed using mutual information, the embedding dimension using false nearest neighbors, and a radius yielding a recurrence rate between 3-5%, as suggested by [36]. In this study, we estimated these parameters from the data, separately from wrist and head, and obtained a delay of 88 (wrist) and 89 (head), a radius of 120.7 (wrist), 14.1 (head), and an embedding dimension of 2 in both body parts. We computed windowed cross-recurrence to track how the recurrence rate observed between the two participants, changes over the course of a single trial. Note, in this analysis, recurrence rate is computed only along the diagonals of the RP, which convey information about the synchronization, as said above. In order to control for the variability induced by the turn-taking task, we divide the time-course of a trial into 6 intervals, and run windowed-cross recurrence in each interval. Each interval is calculated from the moment the leader grasps the block to be stacked until the follower puts his/her block afterwards. As there are 12 blocks to be put, there are 6 of such intervals. Finally, we also examine the recurrence rate observed at the main diagonal of the C/RP (Line of Coincidence) and its close surrounding, which reflects the two time-series (e.g., the velocity profile for the head of the follower and the leader) visiting the same state at the same time (at the LOC), or on a small range of lags around it (the diagonals off the LOC). The diagonal-wise recurrence is used to show whether there is a leading-follower pattern within a certain time-frame [32]; and, for our purposes, establish whether there are differences between head and wrist. We utilize the R package crqa [28], which shows perfect comparability with the widely known crptoolbox (MATLAB) by Norbert Marwan.

C. *Statistical analyses*

In order to assess statistical significance, we utilize linear-mixed effect models, a hierarchical regression accounting for the variability of random variables related to sampling [37], e.g., Dyads. We build mixed-effects models with full fixed effects structure (i.e., all main effects and their interactions) with maximal random structure (i.e., random variables included as intercepts and uncorrelated random slopes) an approach known to result in the lowest rate of Type 1 error [38].

The linear predictors included in our models are Session (a continuous variable, ranging from 1 to 10), and Body-Part (a categorical variable with 2 levels, Wrist and Head). When comparing the auto-recurrence between leader and follower, we add a categorical variable Role (coding for Leader and Follower). All variables are centered to reduce co-linearity. For the windowed cross-recurrence instead, we add a continuous variable to account for the Time along which recurrence is tracked. In the tables, we report the coefficients, standard errors, t-values and derive p-values for the fixed effects in the LME models, as calculated from F-test based on Satterthwaite approximation to the effective degrees of freedom [39].

III. RESULTS

A. *RQA measures, comparing auto-recurrence, between leader and follower*

We computed auto-recurrence on the wrist and head velocity profile, separately for the follower and leader, and obtained 4 indexes (L[1], DET, ENTR, LAM) characterizing their dynamics (See Table 1 and Figure 1).

	L		DET		ENTR		LAM	
Dependent Measures	β	t	β	t	β	t	β	t
Intercept	5.99***	24.75	79.24***	83.58	2.01***	57.72	79.20***	73.90
Session	0.2 **	3.31	0.54**	3.25	0.02**	3.43	0.31°	1.67
Bodypart	2.45***	5.17	−26.86***	−18.37	0.15*	2.44	−31.45***	−18.66
Role	0.48	1.1	3.75***	3.48	0.06	1.38	2.73*	2.21
Session:Bodypart	0.25*	2.54	0.48	1.48	0.02	1.78	0.43	1.21
Session:Role	0.19*	1.95	0.72*	2.21	0.02*	2.22	0.77*	2.15
Bodypart:Role	0.77	1.36	5.7 **	3.07	0.06	0.98	5.01*	2.46
Session:Bodypart:Role	0.38*	1.92	2.15**	3.31	0.06*	2.56	2.11*	2.97

○ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[1] We decided not to report RR because, as said above, it gives an estimate of indiscriminate alignment, i.e., there is no directionality, while especially for C/RQA directionality plays a major role

Table 1. Auto-recurrence: comparing individual parameters of synchronism between leader and follower, on head and wrist across sessions. Coefficients of mixed-effects models with maximal random structure (intercept and slopes on Dyads). Each RQA dependent measure, L, DET, ENTR and LAM, is organized across columns, is modeled as a function of the centered and contrast coded predictors: Bodypart (Head = -.5, Wrist = .5), Role (Follower = -.5, Leader = .5) and Session (a continuous variable from 1 to 10). We report the β with the associated p-value, and the t-value from which it was derived.

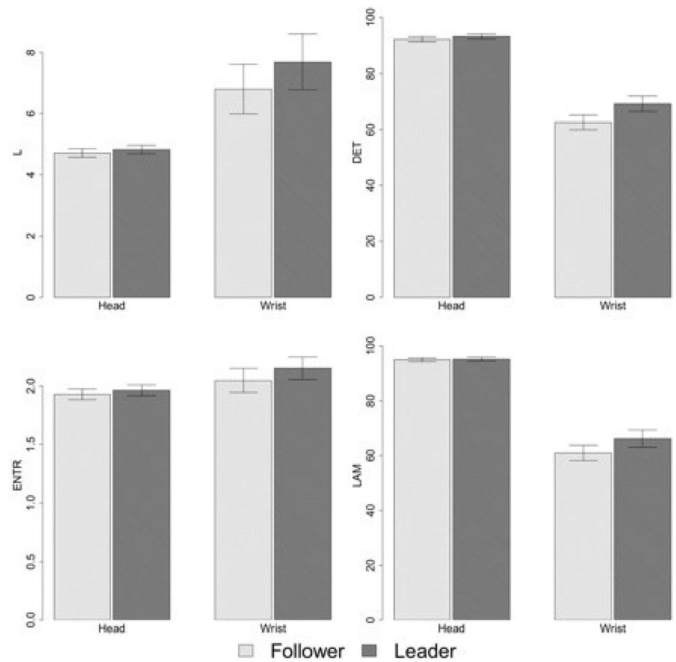

Fig 1: Bar plots for the RQA measures of L (length of the diagonal line), DET (percentage determinism), ENTR (entropy) and LAM (laminarity) mean and 95% CI, characterizing the movement dynamics of head and wrist (represented as a velocity profile) separately for Follower (light gray) and Leader (dark grey).

First, we look at the average length of the diagonal (L), which, to reiterate, indexes the temporal duration of the time-series to be in synchrony with itself (or with another series in the cross-recurrence case), for the leader and follower as independently considered (i.e., auto-recurrence). Here, we find a main effect of Session, whereby the lines get longer the more trials have been completed, which indicates that participants learn to overall better synchronize along the experimental session. We also observe a main effect of Bodypart, whereby, we observe longer lines for the wrist as compared to the head. This result is not surprising as the wrist is the body part more directly engaged, and strictly constrained by the task. More interesting results concern the interactions between Session, Role and Bodypart. In particular, we find that over the experimental session, lines get longer for the Wrist than for the Head (two-ways Session:Bodypart), the Leader becomes more synchronous than the Follower over the session (two-way interaction Session:Role), especially on the Wrist (three-ways interaction Session:Bodypart:Role).

When looking at the determinism (DET), which indexes the predictability of behavior, we find a main effect of Session, meaning that both leader and follower become more predictable during the course of their interaction. We also observe a main effect of Bodypart, whereby the Wrist is less predictable than the Head, and a main effect of Role, where the Leader is more predictable than the Follower. When looking at the interactions, we find that the Wrist becomes more predictable as a function of the Sessions (two-ways interaction Session:Bodypart), especially for the Leader (three-ways interaction Session:Bodypart:Role; Figure 2). We also observe a two-way interaction between Bodypart and Role, whereby, the Leader is more predictable than Follower, on its Wrist movement.

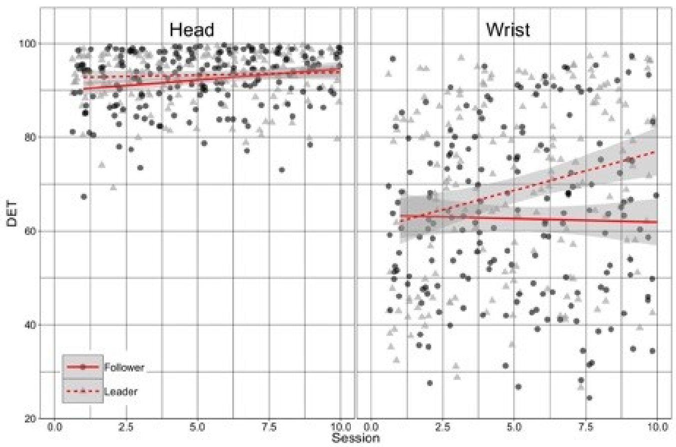

Fig 2: RQA scatter-plot of DET (y-axis) as a function of the number of Session (x-axis). We use point and line type to mark the Leader (triangle-dashed) and the Follower (circle-solid), divided in the two panels according to the body part (Head – left panel; Wrist – right panel). The lines represent the mean estimates (and standard errors as shaded bands) of a generalized linear model fit to the data.

On the Entropy, we find that the Wrist has a more entropic pattern than the Head, the Leader is more entropic than the Follower, especially as the Session progresses and on the Wrist more than on the Head. When looking at laminarity, i.e., how repetitive is the system, we largely corroborate the results on determinism: more repetitive responses as a function of the sessions, the head more repetitive than the wrist, the leader more repetitive than the follower. The wrist becomes more repetitive as a function of the session, especially in the leader.

B. C/RQA measures

Moving to the Cross Recurrence analyses (Table 2), on L we observe that the dyads coordinate more strongly on their Wrist movement, than on their Head movement, but their Head coordination increases over the experimental Session. On DET, we corroborate the main effect of Session, with dyads becoming more predictable as a function of the experimental progress, and the overall higher predictability of the Wrist over the Head. When looking at the Entropy, we find the Wrist to be more entropic than the Head, even though, entropy for the Wrist decreases over the experimental Session (i.e., the two-way interaction Session:Bodypart).

	L		DET		ENTR		LAM	
Dependent Measures	β	t	β	t	β	t	β	t
Intercept	4.04^{***}	29.5	89.93^{***}	96.85	1.8^{***}	35.07	95.78^{***}	232.65
Session	0	−0.58	0.11^{**}	1.1	0	−1.15	0.15^{*}	2.31
Bodypart	0.79^{***}	8.65	2.07°	1.76	0.27^{***}	5.59	1.15^{*}	2.04
Session:Bodypart	-0.05^{*}	−2.95	−0.21	−1.59	-0.02^{***}	−3.4	-0.3^{*}	−2.34

○ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2. Cross-recurrence: quantifying the dyad's synchronism on head and wrist across sessions. Coefficients of mixed-effects models with maximal random structure (intercept and slopes on Dyads). Each C/RQA dependent measure, organized across columns, is modeled as a function of the centered and contrast coded predictors: Bodypart (Head = -.5, Wrist = .5) and Session (a continuous variable from 1 to 10). We report the β with the associated p-value, and the t-value from which it was derived.

Finally, when looking at the stability of the system (LAM; Figure 3), we confirm that dyads become more repetitive as a function of the experimental session, especially on the Head, even though, they are overall more stable on their Wrist.

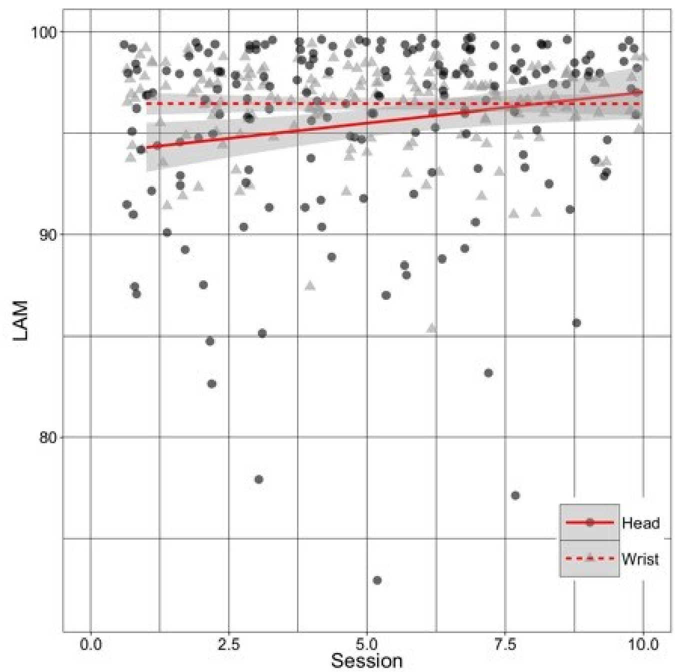

Fig 3: C/RQA scatter-plot of the LAM (y-axis) of the Leader and Follower dyadic interaction, as a function of the number of Session (x-axis). We use point and line type to mark the Wrist (triangle-dashed) and the Head (circle-solid). The lines represent the mean estimates (and standard errors as shaded bands) of a generalized linear model fit to the data.

C. Windowed and diagonal cross-recurrence profiles

Here, we look at how dynamical properties of the interaction change as a function of the time-course within a single trial. In Figure 4, we plot the windowed cross-recurrence across the 6 turn-taking intervals (i.e., from the leader taking the block, till the follower puts his block, please refer to Method for more details about the time-course normalization). It is rather evident from the plot that the Wrist and Head undergo a very different pattern of synchronization across the trial.

In particular, on the Head, we observe synchronization to increase over time, as highlighted by the significant interaction between Bodypart and the linear term of Time1 in Table 3. On the Wrist instead, we observe a clear convex dynamics of synchronization, where the dyad loses coordination and get to a plateau over which adaption to each other's action is learned. Once such convergence is obtained, their coordination sharply increases until the end. This effect is seen in Table 3, as an interaction between BodyPart and the quadratic term of Time.

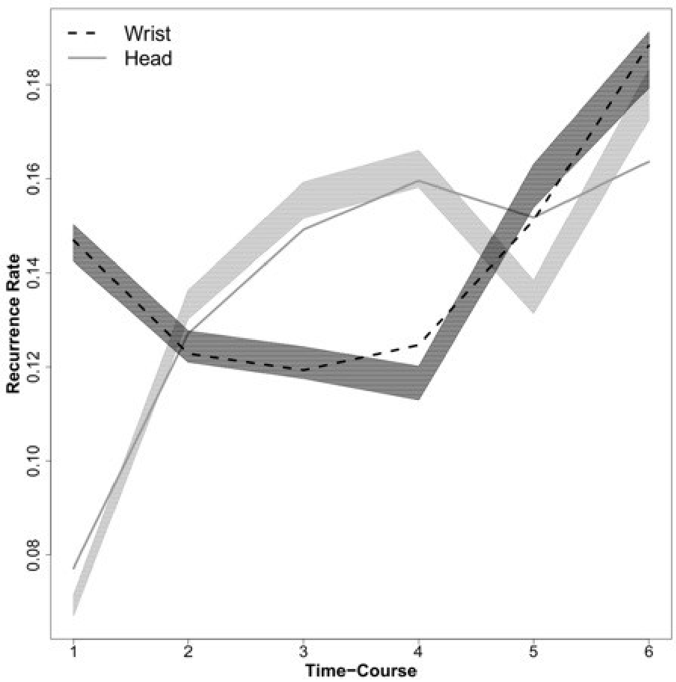

Fig 4: Windowed cross-recurrence analysis of dyad's movement dynamics over a time-course of 6 normalized intervals. The intervals are obtained by windowing the velocity profiles according to the turn-taking intervals between the leader putting his/her block, and the follower putting his/her block afterwards. As there are 12 blocks in total, there are 6 of such intervals. The shaded bands represent the standard-error from the observed mean, whereas the lines are the estimate of the LME model (reported in Table 4) to the data.

Predictor	β	*SE*	*t*	*p*
Intercept	0.11	0.02	7.12	0.0001
Bodypart	0.008	0.01	0.86	0.3
$Time^1$	0.025	0.01	3.01	0.003
$Time^2$	0.004	0.01	0.45	0.6
Bodypart:$Time^1$	-0.02	0.06	-3.87	0.0001
Bodypart:$Time^2$	0.07	0.06	14.16	0.0001

Table 3. Windowed-cross-recurrence: time-course analysis of recurrence rate during the individual trial, as predicted by Time (1- 6 intervals) represented as an orthogonal polynomial of order two (Linear, Time1; and Quadratic, Time2) and Bodypart (Head = -.5 and Wrist = .5). Random intercepts of Dyads and Random slopes for main effects were included in the model. We report beta, standard error, t and p-values of our predictors.

When looking more in depth at the measures characterizing this pattern (refer to Table 4), we find that the dyads display longer average diagonal length in their Wrist than in their Head, and overall longer over the course of the trial, as indicated by the main effect of Time. Interestingly, the length of their synchronization gets stronger for the Wrist than for the Head within the trial (two-ways interaction, Bodypart:Time), even though, across the Session, it is on the Head, rather than on Wrist, that we observe a more prominent strengthening of such synchronization (three-ways interaction Session:Bodypart:Time). On determinism, we largely confirm the results observed on L. In fact, the Wrist is more predictable than the Head, even though, the Head becomes more predictable within the trial, and across the sessions. On the Entropy, we observe more entropic phases of synchronization for the Wrist than the Head, and the latter becomes more entropic across the trials. Finally, on the Laminarity, we confirm again that the Wrist is more repetitive than the Head, but the Head becomes more repetitive within, and across the sessions (refer to Table 4 for the model coefficients).

	L		DET		ENTR		LAM	
Dependent Measures	β	t	β	t	β	t	β	t
Intercept	3.72***	27.57	86.67***	75.74	1.5 ***	25.94	93.47***	123.93
Session	−0.01	−0.81	0.14	1.14	0	−1.11	0.08	0.67
Bodypart	0.78***	8.06	3.13*	2.28	0.28***	5.71	2.51*	2.55
Time	0.48***	5.53	0.77	0.2	0.76***	5.58	−6.47*	−2.46
Bodypart:Time	2.87***	19.84	−18.06***	−16.85	−0.24***	−5.3	−6.15***	−6.41
Session:Time	−0.08**	−3.37	0.30	0.11	0	−0.34	0.33*	1.96
Session:Bodypart	−0.02***	−5.17	−0.17***	−4.13	−0.01***	−4.43	−0.33***	−8.67
Session:Bodypart:Time	−0.44***	−9.31	−3.07***	−8.25	−0.12***	−8.2	−2.44***	−7.32

∘ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4. Windowed-cross-recurrence: C/RQA measures of the dyad's interaction as a function of the time of trial, and across the sessions, comparing head and wrist across sessions. Coefficients of mixed effects models with maximal random structure (intercept and slopes on Dyads). Each C/RQA dependent measure, organized across columns, is modelled as a function of the centred and contrast coded predictors: Bodypart (Head = -.5, Wrist = .5), Session (a continuous variable from 1 to 10). Time (a continuous variable indicating the normalized time course of the trial). We report the b with the associated p-value, and the t-value from which it was derived.

We conclude our examination of the synchronization dynamics underlying the interaction of the dyad on the head and the wrist by looking at the diagonal-wise cross-recurrence profile (150 normalized time-lags around the LoC), which provides us with the directionality of synchronization within the dyad. We find stronger synchronism on the wrist and maximal recurrence is observed at short lags. This indicates that there is not a particularly prominent leader-follower dynamic on this movement, which reflects the rigidly turn-taking nature of the block-stacking task. On the Head, instead, we observe greater recurrence on the side of the leader (i.e., positive lags), which indicates that the follower tends to reactively respond to the leader's head movement.

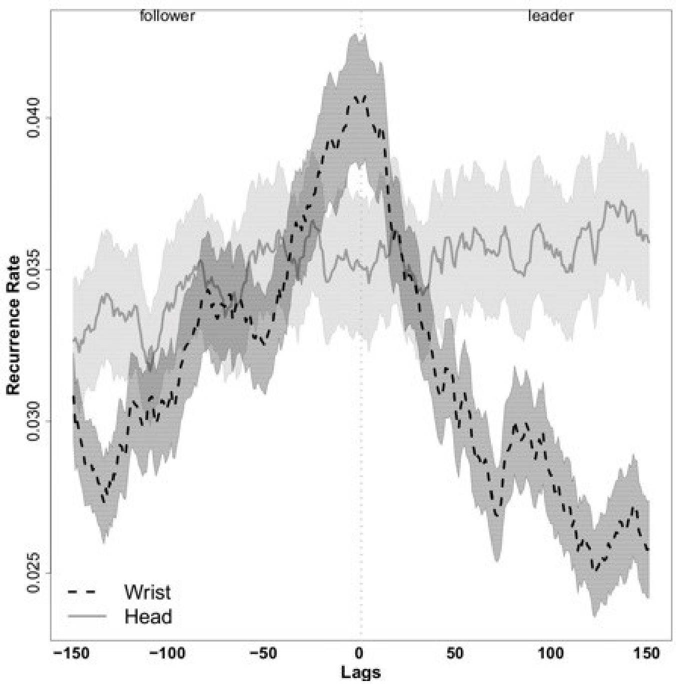

Fig 5: Diagonal-wise cross-recurrence of the velocity profiles of the leader and follower as a function of the lag (±150), for Head (light-gray, solid), and Wrist (black-dashed). Recurrence ranges from 0 to 1, with 1 indicating perfect recurrence between leaders and followers. Lines represent means, and the shaded bands the standard errors around the means.

IV. Discussions

C/RQA measures the regularity and stability of a dynamical system, such as the bodily-movement of an individual (auto-recurrence), or the coupling dynamics between two interacting individuals (cross-recurrence). In this study, we investigated the dynamics of sensorimotor convergence of a dyad engaged in a turn-taking block-stacking task. We examined whether dynamics differ between body parts (wrist Vs head velocity profiles), vary according to the role performed in the task (leader Vs follower) and especially whether synchronization changes as a function of experience with the task, both within a single trial and across the entire experimental session. Among the most important findings, we found that the auto-recurrence in the wrist movement of the leader increases more than the one of the follower throughout the task (Figure 1 and 2). These results confirm our previous study showing larger auto-correlation in leaders' wrist behavior [20] and is in agreement with similar research showing reduced variability in the leader's performance [40]. Stronger auto-recurrence (L, DET and LAM indexes) in the leader's movement implies that he/she was more consistent in his/her arm-reaching action, and that this consistency was refined already with just few trials. Notably, auto-recurrence significantly increases notwithstanding the fact that roles alternated within the experimental session. This shows that this effect is particularly powerful and substantially driven by the specific role played in each individual trial. Indeed, the follower had to choose the next cube depending on the behavior of the leader, and this might have introduced a larger uncertainty in his/her motor-planning resulting into a flat auto-recurrence across the experimental session. At the same time, however, the increase in auto-recurrence in the leader may have resulted in a better predictability of his/her behavior [41], thus implicitly helping the follower to synchronize with him/her [42]. This interesting result suggests that the two body parts are subject to a quite different pattern of time-dependent learning based on the task role. In fact, when looking at the synchronization dynamics of the dyad within a single trial, as well as across the experimental session, we observe a remarkably different evolution for the head and the wrist.

In particular, a C/RQA analysis of the leader and follower movements quantifying their joint synchronization shows that the dyad improves their head synchronization over the experimental session more than the wrist, as indicated by L, DET and LAM measures in Table 2 and Figure 3, even though it became more entropic. Moreover, when synchronism is tracked within a single trial using windowed-cross recurrence, we find that the dyads' head motion steadily increases over the time-course, whereas wrist motion displays an initial decrease, it stabilizes mid-course, and presents a sharp increase during the final phase (see Figure 4). Considering that head motion is not directly necessary for the task, and thus relatively free to vary across trials and participants, it is interesting to observe such increase in synchronism. In fact, if task performance is optimized uniquely on instrumental movements (hand grasping and arm reaching movements) then, we would not have observed entrainment in the heads of the dyad. However, as discussed in the introduction, head movements index 'supra-segmental' aspects of sensorimotor interaction such as emotional and affective states, as well as, joint task engagement [22]. In the context of this task, head synchronization might have served the dyad to manifest consensus about the moves used to build the tower, as well as, construct mutual trust. Synchronization on the wrist, instead, was more independently construed by the leader and the follower, as shown in the RQA analysis above mentioned, and important at the beginning and the end of each individual trial, as shown in the windowed cross-recurrence analysis.

When we examined the directionality of synchronism by looking at the diagonal-wise cross recurrence profile, we observed another interesting dissociation between head and wrist (Figure 5). The wrist motion showed maximal recurrence around very short lags, whereas the head was characterized by a rather uniform distribution across both short and long lags, and was on average larger on the leaders' side. This fact further corroborates the idea that head motion is potentially capturing "supra-segmental" aspects of sensorimotor interaction, which are supposed to promote entrainment of larger and slower behaviors (i.e. whole body sway as opposed to arm reaching).

Taken together, these results seem to suggest that the dyad employed a variety of different coordination strategies to produce a successful cooperation. On one hand, the leader produced a predictable wrist signal to facilitate the follower, in line with previous results [6-8,20,40-42]. On the other hand, the follower tended to reactively align his/her head motion with the leader, with the likely goal of building consensus with him/her. This idea is supported also by the increased head motion synchronism within the time-course of a single trial.

These results strongly suggest that dyadic interaction in a complex and ecologically valid task happens at multiple levels and time-scales. Here, we described the dynamics of interaction between a leader and follower at two time-scales: instrumental movements (wrist) and ancillary movements (head). However, there are several other levels arising from interpersonal interaction, such as its context, the task goals entailed, motivational factors and individual differences, which make the investigation of human-to-human interaction an almost intractable problem. A classic approach to simplify such complexity is to assume a fix scenario and task constraints (or free to vary in a predictable manner) and let individual differences be the "only" free parameter. Despite this solution can shed light on joint-actions, and can be successfully used to test specific hypotheses, it is an approach that does not grant any form of generalization, i.e., context-independence.

In fact, generalization across tasks and contexts can occur solely by digging out principles of social interaction. In the present paper, we precisely looked at sensorimotor convergence as a promising approach to tackle the complexity of social interaction, and achieve context independence. We based this idea on neuroscientific evidences suggesting that the sensorimotor level provides the building blocks for high-levels cognitive mechanisms [43]. Indeed, the neural circuits of the so called mirror system [44] seem to be a necessary prerequisite to turn other (motor) behavior into motor representations usable to plan cooperative behavior [45]. Furthermore, there are growing behavioral evidences suggesting that sensorimotor convergence is automatic, and happens on movement parameters, which are rather independent from task and context constraint [13-14-20]. In this study, we follow this route, and showed that this could be a promising solution to obtain a more integrated understanding of the principles dominating behavioral coordination among human agents.

Additionally, we have grounded our measurements of behavioral coordination within an ecologically valid scenario. We devised a game-like scenario where participants actively engaged in a task fostering a natural cooperative behavior. The task was natural because it did not require training of participants, nor the use of well-constrained instructions, and it was short enough to maintain them engaged with it (about 20 minutes including setting it up). Moreover, the data recording was minimally invasive, nor affected participants' movements (small reflective markers and no cabling), and can be potentially obtained with cheaper and even less intrusive technologies (i.e. Kinect). Beside its relevance for investigating interpersonal coordination at sensorimotor level, the proposed task may be also useful to evaluate whether and to which extent subjective dimensions of partners' engagement, such as the experience of "flow" [46] and social presence (i.e. feelings of mental connectedness), modulate dyadic movement dynamics and performance [47].

Furthermore, the simplicity of our task, i.e., a block-stacking task, offer the practical advantage of tapping into sensorimotor interaction during ecological joint action while being easy to standardize across different computational methods and/or recording equipment. This step is necessary to extrapolate insights from HHI that can be directly applied in HRI research. In fact, some characteristics of our task also allow a clear transition between HHI and HRI research. First of all, the visual features of the objects used in the task, can be easily recognized by computer vision systems Also, object affordances are compatible with the grasping dexterity of most robotic hands. Arm range of motion is designed to fit the reaching capabilities of most robotic platforms. The task space is not ambiguous, as it can be represented with a hierarchical plan where the final goal is to obtain a tower by placing single cubes (i.e. sub-goals). Finally, a clear success metric is present and it is based on the time to execute the tower. We believe that results on such a standardized HHI task could offer an invaluable benchmark to investigate HRI across robotic platforms and algorithmic implementations. In particular, as there are multiple ways to read parameters of human action, and several ways to plan appropriate cooperative behavior, different HRI control schemas can be tested to find the one eliciting an output directly comparable with HHI benchmarks.

We also foresee alternative, perhaps more ambitious, uses of such a HHI baselines. In first approximation, the automatic system reads human motion data and, with the shortest lag possible, plans its own action to be optimally timed and coupled to that of the human participant. The robotic system, here merely interprets human activity but does not try to exert any influence on his/her behavior. In fact, a more ambitious research program would instead try to make such communication bidirectional and dynamical. Behavioral and neurophysiological research on humans tell us that we are particularly sensitive to others' action kinematic modulations [20]. This capacity is critical during joint action, and used to predict others' action goals [48] or intentions [3]. More importantly, these small kinematic modulations are used to signal to the interactive partner, critical task information [6]. Based on our current results we could imagine that small modulations in the velocity profiles of the robotic action may be used to encode useful information to optimize the cooperation with humans [14-49]. In fact, the dynamic modulation of the velocity profiles between human and robots would mean the establishment of a basic sensorimotor communicative bi-directionality, of the same kind we quantified here between humans. Importantly, the same robotic controller may be adopted and the amount of Human Robot coupling (as measured with C/RQA for example) could be tracked and used to fine-tune its parameters on a trial-by-trial basis via reinforcement learning. In fact, based on the optimality of HHI, it might be possible to have a bottom-up synthesis of the most efficient robotic arm trajectory, by optimizing/maximizing the amount of bidirectional sensorimotor information transfer between human and artificial agents.

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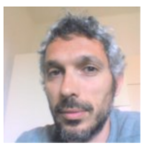

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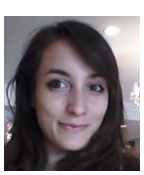

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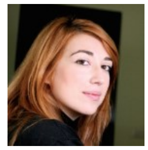

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